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(84) Fuzzy genetic learning automata classifier

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(47) A method is provided for deriving a near-optimal fuzzy automaton for a given separation problem.

The method includes the steps of forming a first generation population (24) of fuzzy automata, where the first generation population of fuzzy automata includes a plurality of fuzzy automata performing a mutation operation (28) on each fuzzy automaton in the first generation population of fuzzy automata reproducing the first generation population of fuzzy automata using a survival of the fittest operation (30, 32, 34) and applying a crossover operator (36) to the reproduced first generation population of fuzzy automata, thereby yielding a next-generation population of fuzzy automata. A near-optimal fuzzy automaton is identified by evaluating the performance (38) of each fuzzy automaton in the next-generation population otherwise the methodology is repeated until a near-optimal fuzzy automaton is derived for the given separation problem.

For two-letter codes and other abbreviations, refer to the "Guidance Notes on Codes and Abbreviations" appearing at the beginning of

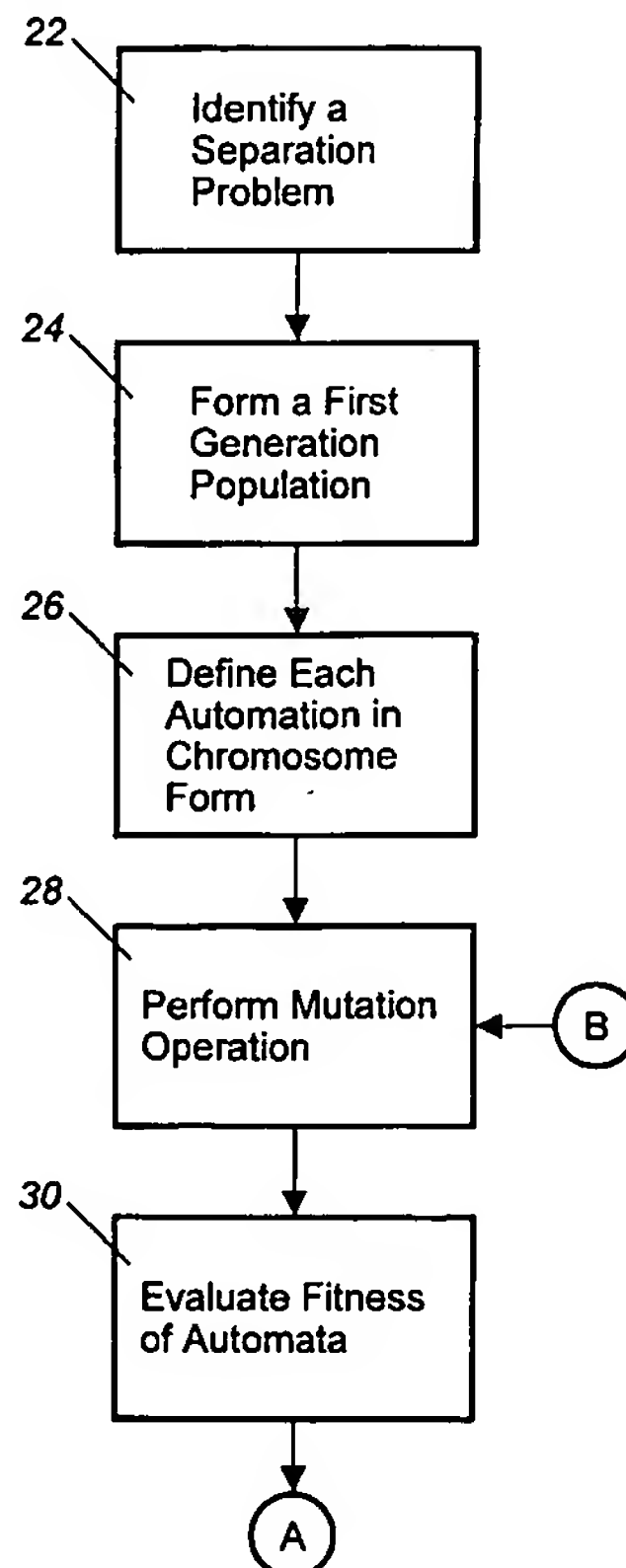


Figure 2A

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WO 01/99043 A1

(54) Title: HEURISTIC METHOD OF CLASSIFICATION

(57) Abstract: The invention concerns heuristic algorithms for the classification of data streams. The invention is useful in the areas of classifying texts and medical sample data.

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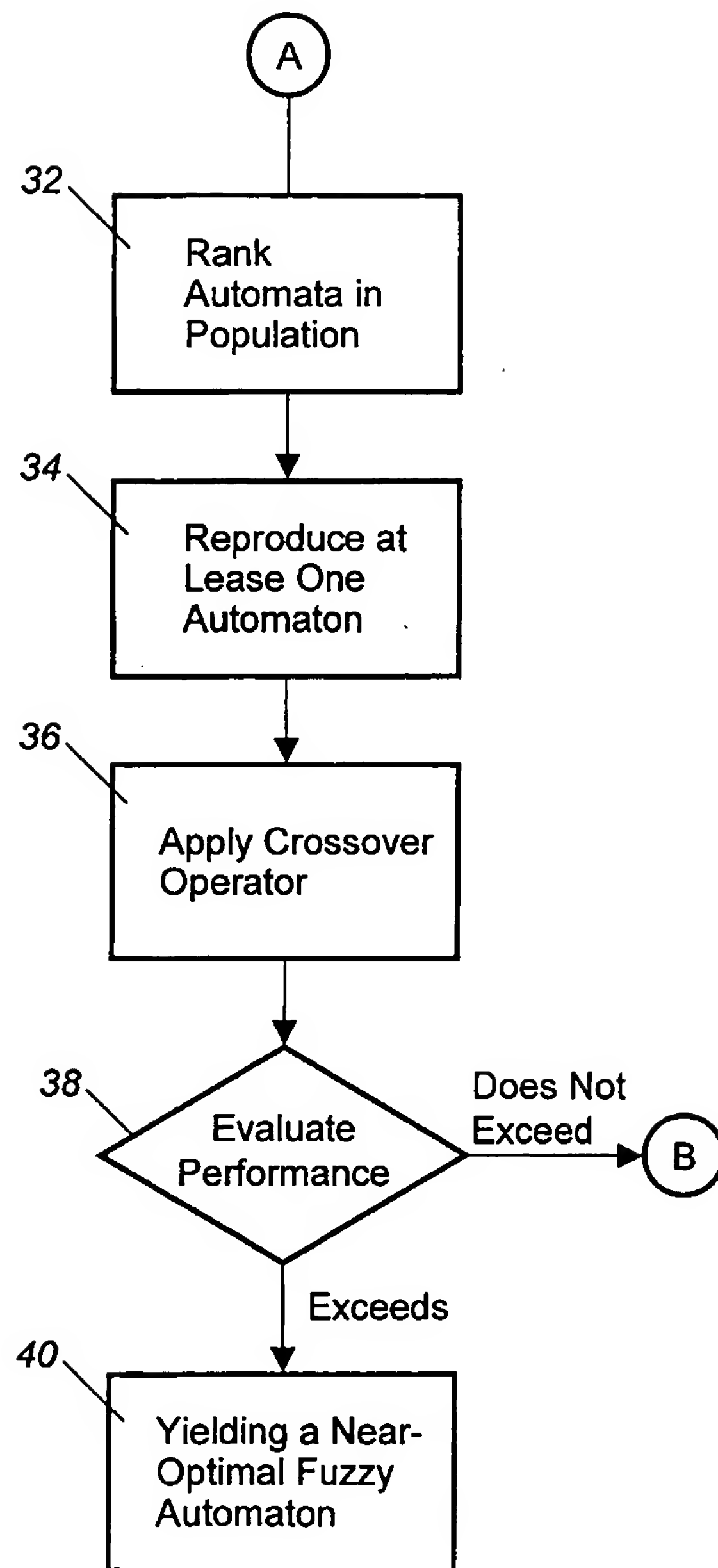


Figure 2B

Description

BACKGROUND OF THE INVENTION**1. Field of the Invention**

[0001] This invention relates generally to signal classifiers, and, more particularly, to a signal classifier which employs fuzzy genetic learning automata.

2. Discussion of the Related Art

[0002] Typical passive sensor systems which collect wideband signals are receiving an enormous flux of information from a continually evolving signal environment. This enormous flux of information threatens to exceed the capacities of the human signal analysts to analyze the data. As a result, there is a pressing need for artificially intelligent systems which quickly analyze the arriving data stream, and, while so doing, effect machine learning in order to adapt to the continual signal-environmental changes. The intelligent systems should filter the signal data by identifying and separating known signals from the arriving flux of signal information. This potentially reduces the workload for the human signal analyst by allowing him/her to focus attention on signal features which are more likely to contain mission-important information.

[0003] Adaptive front-end signal classifiers are generally known in the art. Conventional front-end signal classifiers utilize many inner product-based schemes which compare the arriving signal to a set of basis functions that serve as exemplary signals. These inner product-based schemes may be based on Fourier analysis, wavelets, and/or Gabor transforms. In each of these schemes, the computational intensity is high and there is little flexibility to adapt to a changing signal environment.

[0004] Therefore, it is desirable to provide an adaptive signal classifier which learns to identify specific embedded spatiotemporal signals in an arriving signal data stream of an evolving signal environment. More specifically, it is desirable to implement a signal classifier using fuzzy automata. Fuzzy automata generally use min-max aggregation to process the incoming data, thereby obviating the need for highly intense inner product-based comparisons to exemplary signals. Since each fuzzy automata is a language-learning system, only one requirement needs to be imposed on the signals that are to be acquired: a signal needs to be characterizable as occurring in one or more states and transitioning as a whole or partially among some or all states over time. Thus, the formal language framework of fuzzy automata is particularly well-matched to signal separation applications. In addition, the operation of each fuzzy automaton is independent of the durations of the incoming signals.

SUMMARY OF THE INVENTION

[0005] In accordance with the teachings of the present invention, a method is provided for deriving a near-optimal fuzzy automaton for a given separation problem. The method includes the steps of (a) forming a first generation population of fuzzy automata, where the first generation population of fuzzy automata includes a plurality of fuzzy automata (b) performing a mutation operation on each fuzzy automaton in the first generation population of fuzzy automata (c) reproducing the first generation population of fuzzy automata using a survival of the fittest operation and (d) applying a cross-over operator to the reproduced first generation population of fuzzy automata, thereby yielding a next-generation population of fuzzy automata. A near-optimal fuzzy automaton is identified by evaluating the performance of each fuzzy automaton in the population; otherwise the methodology is repeated until a near-optimal fuzzy automaton is derived for the given separation problem.

[0006] Additional objects, features and advantages of the present invention will become apparent from the following description and appended claims taken in conjunction with the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0007] Figure 1 is a diagram depicting an exemplary signal classifier implemented in accordance with the present invention.

[0008] Figures 2A and 2B are flowcharts illustrating a method for deriving near-optimal fuzzy automata for a given separation problem in accordance with the present invention.

[0009] Figure 3 is a diagram depicting an exemplary crossover operation between two fuzzy automata in accordance with the present invention and

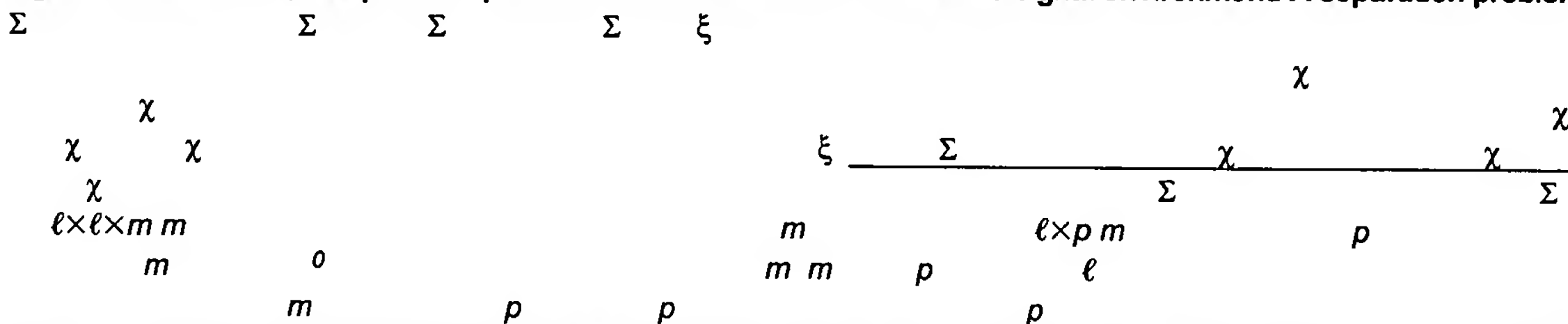
[0010] Figure 4 is a flowchart illustrating a method for deriving a signal classifier in an evolving signal environment in accordance with the present invention.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

[0011] Figure 1 illustrates an exemplary signal classifier 10 that is implemented using fuzzy genetic learning automata in accordance with the present invention. Each of the fuzzy genetic learning automata are dedicated to learning and separating a specific signal or a particular set of signals from an evolving signal environment. As will be apparent to one skilled in the art, two or more fuzzy automata may be used to implement the signal classifier 10. In a preferred embodiment, each of the fuzzy automata are implemented as individual software agents.

[0012] In operation, the signal classifier 10 receives a plurality of input signals 12 from a signal environment. The input signals 12 are evaluated by each of the fuzzy automata. For illustration purposes, a first automaton, $U_{1,3}$, is intended to classify Signals 1 and 3 and distinguish them from Signal 2 whereas a second automaton, U_2 , is intended to classify Signal 2 and distinguish it from Signals 1 and 3. Each fuzzy automaton outputs a confusion matrix, where the rows of the matrix are output vectors arranged according to the input signals. For instance, when Signal 1 is presented to the first automaton, $A_{1,3}$, the first row of the confusion matrix is ideally [1 0 0]. Similarly, when Signal 3 is presented to the first automaton, $A_{1,3}$, the third row of the confusion matrix is ideally [0 0 1]. Likewise, when Signal 2 is presented to the second automaton, A_2 , the second row of the confusion matrix is ideally [0 1 0]. Thus, the resulting output from the signal classifier 10 is an aggregate confusion matrix 14 having the appropriate rows from each of the individual automata. In this example, the first and third rows of the aggregate confusion matrix correspond to the first and third rows of the confusion matrix from the first automaton, and the second row of the aggregate confusion matrix corresponds to the second row of the confusion matrix from the second automaton. It is noteworthy that the aggregate performance of a signal classifier built from two or more fuzzy automata is typically better than the performance of each individual fuzzy automaton.

[0013] A method for deriving a near-optimal fuzzy automaton for a given separation problem is shown in Figures 2A and 2B. In accordance with the present invention, the near-optimal fuzzy automata may then serve as the basis for a signal classifier. First, a separation problem must be identified 22 from the signal environment. A separation problem,



[0014] Initially, an input set of fuzzy automata is chosen stochastically by pulling elements of S , R , and E^0 at random from the unit interval until a set of fuzzy automata with some positive separability is realized. A population of fuzzy automata, $gU^0, gU^1, \dots, gU^\pi$

[0015] A genetic algorithm is iteratively applied to the population of fuzzy automata until a near-optimal fuzzy automaton is derived for the given separation problem. In general, a genetic algorithm is a model of learning which derives its behavior from a metaphor of the processes of evolution as they occur in nature. In nature, the members of a population are derived from and represented by chromosomes. Likewise, the members of a population of fuzzy automata must be represented in a chromosome paradigm in order to apply a genetic algorithm.

[0016] In accordance with the present invention, at least the first three elements of the tuple U , which are ${}_U S$, ${}_U R$, ${}_U E^0$, are redefined 26 in chromosome form. In particular, each data value of each matrix which comprises an element of the fuzzy automaton is represented as a binary word. For example, ${}_U S$ is defined as follows

$$\begin{aligned}
 {}_U S = & \begin{bmatrix} {}_U S_{0,0,0} & {}_U S_{0,1,0} & \cdots & {}_U S_{0,\ell-1,0} \\ {}_U S_{1,0,0} & {}_U S_{1,1,0} & \cdots & {}_U S_{1,\ell-1,0} \\ \vdots & \vdots & & \vdots \\ {}_U S_{\ell-1,0,0} & {}_U S_{\ell-1,1,0} & \cdots & {}_U S_{\ell-1,\ell-1,0} \end{bmatrix} \begin{bmatrix} {}_U S_{0,0,1} & {}_U S_{0,1,1} & \cdots & {}_U S_{0,\ell-1,1} \\ {}_U S_{1,0,1} & {}_U S_{1,1,1} & \cdots & {}_U S_{1,\ell-1,1} \\ \vdots & \vdots & & \vdots \\ {}_U S_{\ell-1,0,1} & {}_U S_{\ell-1,1,1} & \cdots & {}_U S_{\ell-1,\ell-1,1} \end{bmatrix} \\
 & \cdots \begin{bmatrix} {}_U S_{0,0,m-1} & {}_U S_{0,1,m-1} & \cdots & {}_U S_{0,\ell-1,m-1} \\ {}_U S_{1,0,m-1} & {}_U S_{1,1,m-1} & \cdots & {}_U S_{1,\ell-1,m-1} \\ \vdots & \vdots & & \vdots \\ {}_U S_{\ell-1,0,m-1} & {}_U S_{\ell-1,1,m-1} & \cdots & {}_U S_{\ell-1,\ell-1,m-1} \end{bmatrix}
 \end{aligned}$$

where each data value is

$${}_U S_{h,i,j} = ({}_U S_{h,i,j})_0 \circ ({}_U S_{h,i,j})_1 \circ \cdots \circ ({}_U S_{h,i,j})_{n-1}$$

such that each term $({}_U S_{h,i,j})$ in the concatenation is an element of $\{0, 1\}$ and \circ is the concatenation operator. Accordingly, each data value, ${}_U S_{h,i,j}$, of the matrix is a chromosome, e.g., 00101...0011, of some length n . As will be apparent to one skilled in the art, ${}_U R$ and ${}_U E^0$ can be similarly redefined in chromosome form.

[0017] A mutation operation can then be applied to each of the fuzzy automata in the population. To effect mutation, a small number of data entries in S , R , and E^0

$$\begin{array}{ccccccc}
 \chi & & \pi\pi & \rightarrow & \chi & & \chi & & \chi \\
 \chi & \rightarrow & \pi & \chi & \pi & \chi & \pi & \chi & \chi \\
 \pi b & b 1 m & u l o 2 & b & m m b & o 0 1 & p & m b o & m & m u & o & o & l & o & u & m
 \end{array}$$

[0018] For illustration purposes, consider a $2 \times 4 \times 3$ fuzzy automaton where the random entries chosen for mutation are marked with a star as follows

$$\left\{ \begin{bmatrix} \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{bmatrix}, \begin{bmatrix} \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{bmatrix}, \begin{bmatrix} \cdot & \cdot & \cdot & * \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{bmatrix}, \begin{bmatrix} \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{bmatrix} \right\}$$

Thus, there are two data entries where mutation by bit flipping occurs ${}_U S_{1,1,0}$ and ${}_U R_{0,2}$. Within each data entry, a random location is then selected. For example, suppose that the third bit is flipped for ${}_U S_{1,1,0}$ and the fifth bit is flipped for ${}_U R_{0,2}$. The resulting mutation operation would be as follows

$$(U^{S_{1,1,0}})_0 \circ (U^{S_{1,1,0}})_1 \circ (U^{S_{1,1,0}})_2 \circ \dots \circ (U^{S_{1,1,0}})_7 \Rightarrow$$

$$(U^{S_{1,1,0}})_0 \circ (U^{S_{1,1,0}})_1 \circ \mathfrak{I}((U^{S_{1,1,0}})_2) \circ \dots \circ (U^{S_{1,1,0}})_7$$

and

$$(U^{r_{0,2}})_0 \circ (U^{r_{0,2}})_1 \circ (U^{r_{0,2}})_2 \circ \dots \circ (U^{r_{0,2}})_7 \Rightarrow$$

$$(U^{r_{0,2}})_0 \circ (U^{r_{0,2}})_1 \circ \dots \circ \mathfrak{I}((U^{r_{0,2}})_5) \circ (U^{r_{0,2}})_6 \circ (U^{r_{0,2}})_7.$$

One skilled in the art will readily recognize that the above description is merely exemplary of a mutation operation. It is envisioned that other rules may be devised for effecting a mutation operation within the scope of the present invention.

[0019] Next, the first generation population of fuzzy automata is reproduced in accordance with a survival of the fittest operation. As will be more fully explained below, reproduction involves the following three steps (1) evaluating the fitness of each fuzzy automata in the population, (2) ranking the fuzzy automata within the population according to the fitness of each fuzzy automata, and (3) reproducing at least one of the fuzzy automata in accordance with some reproduction rule.

[0020] First, each of the fuzzy automata are evaluated for fitness via a fitness function. In a preferred embodiment of the present invention, the fitness of each fuzzy automaton is assessed using a diagonal dominance indicator. While the following description is provided with reference to a particular fitness function, it is envisioned that other known fitness functions fall within the broader aspects of the present invention.

[0021] In order to determine a diagonal dominance indicator for a fuzzy automaton, a set of input signals must be identified from the signal environment. The set of input signals are evaluated by each fuzzy automaton in the population, thereby yielding a confusion matrix for each fuzzy automaton. A diagonal dominance indicator is computed for each confusion matrix, where a figure of merit for diagonal dominance, D, is provided as follows

$$D = (C_{\text{smallest on-diagonal}} - C_{\text{largest off-diagonal}}) / ((C_{\text{smallest on-diagonal}} + C_{\text{largest off-diagonal}})/2).$$

For illustration purposes, the diagonal dominance indicator for an exemplary confusion matrix of

$$\begin{bmatrix} 1.17 & .21 & .23 \\ .00 & 1.24 & .36 \\ .10 & .22 & 1.26 \end{bmatrix}$$

is computed as $D = (1.17 - 0.36)/((1.17 + 0.36)/2) = 1.06$. As will be apparent to one skilled in the art, a diagonal dominance indicator for a confusion matrix may be computed in accordance with other known figures of merit.

[0022] Second, each of the fuzzy automata in the population are ranked according to the fitness of the individual automaton, where the diagonal dominance indicator is indicative of the fitness of an automaton. More specifically, the fuzzy automata are ranked from the fuzzy automata having the largest diagonal dominance to the fuzzy automata having the smallest diagonal dominance.

[0023] Third, at least one of the fuzzy automata in the population is reproduced in accordance with a reproduction rule. In accordance with a survival of the fittest approach, the reproduction rule is fashioned such that the highest ranked fuzzy automata are reproduced and the poorest ranked automata are eliminated. For example, given a pop-

ulation of eight fuzzy automata, an exemplary reproduction rule may specify that the two highest ranking automata are duplicated, the four middle ranking automata are maintained, and the lowest two ranking automata are eliminated. This exemplary reproduction rule is illustrated as follows

5

$$(\quad) \Rightarrow$$

10 This particular reproduction rule has the advantage of maintaining a constant population size of eight. It is envisioned that other types of reproduction rules fall within the scope of the present invention.

[0024] Once the population of fuzzy automata is reproduced in accordance with a survival of the fittest operation, a unique crossover operator may be applied 36 to the population of fuzzy automata. In general, fuzzy automata crossover operates on two fuzzy automata, U and V, from a particular generation of automata, and produces two new fuzzy automata, W and , belonging to a next generation of the population. More specifically, the crossover operator is specified as a transform Ξ_{Ψ} χ π π π (\quad) π π ξ

15

$$(\quad \Xi)$$

$$\chi$$

$$\pi$$

$$\pi$$

$$\xi\pi$$

20

$$\Xi_{\Psi}((\quad))(\quad \Xi)$$

25

[0025] In the transform Ξ_{Ψ} χ π π π (\quad) π π ξ A^* and B^* are not involved in the crossover operation. Ψ π Ψ $(\Psi_{\Sigma} \Psi \Psi)$ $\Psi_{\Sigma} \Psi \Psi$ χ χ

30

$$\Psi_S = \begin{bmatrix} k_{S;0,0,0} & k_{S;0,1,0} & \cdots & k_{S;0,\ell-1,0} \\ k_{S;1,0,0} & k_{S;1,1,0} & \cdots & k_{S;1,\ell-1,0} \\ \vdots & \vdots & \ddots & \vdots \\ k_{S;\ell-1,0,0} & k_{S;\ell-1,1,0} & \cdots & k_{S;\ell-1,\ell-1,0} \end{bmatrix} \begin{bmatrix} k_{S;0,0,1} & k_{S;0,1,1} & \cdots & k_{S;0,\ell-1,1} \\ k_{S;1,0,1} & k_{S;1,1,1} & \cdots & k_{S;1,\ell-1,1} \\ \vdots & \vdots & \ddots & \vdots \\ k_{S;\ell-1,0,1} & k_{S;\ell-1,1,1} & \cdots & k_{S;\ell-1,\ell-1,1} \end{bmatrix}$$

35

40

$$\cdots \begin{bmatrix} k_{S;0,0,m-1} & k_{S;0,1,m-1} & \cdots & k_{S;0,\ell-1,m-1} \\ k_{S;1,0,m-1} & k_{S;1,1,m-1} & \cdots & k_{S;1,\ell-1,m-1} \\ \vdots & \vdots & \ddots & \vdots \\ k_{S;\ell-1,0,m-1} & k_{S;\ell-1,1,m-1} & \cdots & k_{S;\ell-1,\ell-1,m-1} \end{bmatrix}$$

45

50

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$$\Psi_R = \begin{bmatrix} k_{R;0,0} & k_{R;0,1} & \cdots & k_{R;0,p-1} \\ k_{R;1,0} & k_{R;1,1} & \cdots & k_{R;1,p-1} \\ \vdots & \vdots & & \vdots \\ k_{R;\ell-1,0} & k_{R;\ell-1,1} & \cdots & k_{R;\ell-1,p-1} \end{bmatrix}$$

$$\Psi_{E_0} = [k_{E_0;0} \quad k_{E_0;1} \quad \cdots \quad k_{E_0;\ell-1}]$$

[0026] The operation of the transform $\Xi_{\Psi} \chi$ Ξ $\xi \pi$ $\pi \chi$ Ψ π χ χ

$$w^{S_{h,i,j}} = (u^{S_{h,i,j}})_0 \circ (u^{S_{h,i,j}})_1 \circ \cdots \circ (u^{S_{h,i,j}})_{k_{S;h,i,j}-1} \circ (v^{S_{h,i,j}})_{k_{S;h,i,j}} \circ \cdots \circ (v^{S_{h,i,j}})_{n-1}$$

χ Σ Σ Σ Σ π Σ π π

Σ Ψ_{Σ} χ π

[0027] The second element of W, w_R , is generated similarly as follows

$$w^{r_{h,i,j}} = (u^{r_{h,i,j}})_0 \circ (u^{r_{h,i,j}})_1 \circ \cdots \circ (u^{r_{h,i,j}})_{k_{R;h,i,j}-1} \circ (v^{r_{h,i,j}})_{k_{R;h,i,j}} \circ \cdots \circ (v^{r_{h,i,j}})_{n-1}$$

for each data value $w^{r_{h,i,j}}$ within w_R . Likewise, the third element of W, w^{E_0} , is generated as follows

$$w^{e_{h,i,j}^0} = (u^{e_{h,i,j}^0})_0 \circ (u^{e_{h,i,j}^0})_1 \circ \cdots \circ (u^{e_{h,i,j}^0})_{k_{E_0;h,i,j}-1} \circ (v^{e_{h,i,j}^0})_{k_{E_0;h,i,j}} \circ \cdots \circ (v^{e_{h,i,j}^0})_{n-1}$$

[0028] The next generation fuzzy automaton, χ , is generated in a similar manner. However, in this instance, the front portion of the chromosome comes from V and the tail portion of the chromosome comes from U . Each element of χ is further expressed below. The first element of χ, χ^S , is generated as follows

$$\chi^{S_{h,i,j}} = (v^{S_{h,i,j}})_0 \circ (v^{S_{h,i,j}})_1 \circ \cdots \circ (v^{S_{h,i,j}})_{k_{S;h,i,j}-1} \circ (u^{S_{h,i,j}})_{k_{S;h,i,j}} \circ \cdots \circ (u^{S_{h,i,j}})_{n-1}$$

for each data value within χ^S . The second element of χ, χ^R , is generated as follows

$$\chi^{r_{h,i,j}} = (v^{r_{h,i,j}})_0 \circ (v^{r_{h,i,j}})_1 \circ \cdots \circ (v^{r_{h,i,j}})_{k_{R;h,i,j}-1} \circ (u^{r_{h,i,j}})_{k_{R;h,i,j}} \circ \cdots \circ (u^{r_{h,i,j}})_{n-1}$$

for each data value R . The third element of E^0 , is generated as follows

$$x_{h,i,j}^0 = (v_{h,i,j}^0)_0 \circ (v_{h,i,j}^0)_1 \circ \dots \circ (v_{h,i,j}^0)_{k_{E^0;h,i,j}-1} \circ (u_{h,i,j}^0)_{k_{E^0;h,i,j}} \circ \dots \circ (u_{h,i,j}^0)_{n-1}$$

for each data value of E^0 . Thus, the crossover transform has been described in complete detail.

[0029] For illustration purposes, an exemplary crossover operation is illustrated below. Suppose U and V are as follows

$$uS = \begin{bmatrix} 0011000000 & 0000100111 \\ 0011011111 & 0011000101 \end{bmatrix} \begin{bmatrix} 0001101010 & 0011111011 \\ 0001101001 & 0000100011 \end{bmatrix},$$

$$vS = \begin{bmatrix} 0100010110 & 0010110101 \\ 0000110000 & 0001011011 \end{bmatrix} \begin{bmatrix} 0010011011 & 0011100000 \\ 0000101011 & 0000111101 \end{bmatrix},$$

uR , vR , and uE^0 , vE^0 . In addition, the crossover allele, Ψ

$$\Psi_S = \begin{bmatrix} 8 & 8 \\ 8 & 8 \end{bmatrix} \begin{bmatrix} 8 & 8 \\ 8 & 8 \end{bmatrix},$$

$$\begin{array}{cccccccccccc} \Psi & \Psi & & \chi & & \pi & & \Xi_\Psi & & \pi & \chi & \Xi \\ & & & & & & \chi & \pi & & & & \\ \pi\pi & & \pi & & \chi & & \pi & & & & & \chi \\ \pi & & & \Xi & \chi & & \pi & & & & \chi & \pi \\ & & & & \chi & & \chi & & \Sigma & & \chi & \pi \\ & & \Sigma & & \chi & & \chi & & \chi & & & \Sigma \end{array}$$

[0030] Although the present invention is not limited as such, the above-described crossover operation is applied to the first generation population of fuzzy automata by randomly selecting pairs of fuzzy automata from the population and then applying the crossover operator to each pair of fuzzy automata. For a population of eight fuzzy automata, the crossover operator is applied to four randomly selected pairs of fuzzy automata. In this way, a next generation population of fuzzy automata have been derived for the given separation problem.

[0031] Lastly, each of the fuzzy automata in the next generation population is evaluated for performance 38 in view of the given separation problem. In a preferred embodiment, each fuzzy automaton is evaluated using the above-described fitness function. If one of the fuzzy automata exceeds some predefined performance threshold (e.g., a minimum diagonal dominance value), then algorithm is complete, thereby yielding a near-optimal fuzzy automaton 40 for the given separation problem. On the other hand, if none of the fuzzy automata in the next-generation population exceeded the performance threshold, then the process is repeated starting with the next-generation population serving as the input to the mutation operation. The genetic algorithm of the present invention can be repeated until at least one fuzzy automaton exceeds the performance threshold associated with the given separation problem. As will be apparent to one skilled in the art, employing a genetic algorithm having the basic elements of mutation, reproduction of the fittest, and crossover guarantees convergence upon a near-optimal solution for the given separation problem. While the above description of the present invention has been provided with reference to a particular genetic algorithm, there are other known generation-level genetic operations (e.g., blended crossover, gray coding, etc.) which may be incorporated into the overall framework of the present invention.

[0032] A signal environment, $\in \tau$ $\tau \pi \chi$ τ τ
 τ τ τ τ $\tau \tau$ τ τ
 τ τ (χ τ $\pi \chi$) $\chi \chi$ τ π τ π $\Sigma(\tau)$ $\tau \pi \chi$
 τ

[0033] Referring to Figure 4, a method is provided for deriving a signal classifier in an evolving signal environment. As previously described, a single fuzzy automaton at a fixed epoch in history τ τ τ χ τ

$$\begin{array}{ccccccccccccccccccc}
 \tau & \tau & & & \tau & & \tau & \tau & & \tau & \tau & & \tau & \tau\chi & & \tau & & \tau & \tau & \tau \\
 & & \tau & & \tau\pi & & \tau & \tau & & \tau & & \tau & \pi & \tau & \pi & & \tau & \tau & \pi & \tau & \pi & \Sigma \\
 (\tau) & & \pi & \tau\tau & & \tau & & \tau & \pi & \tau & \pi & & (\Sigma(\tau)) & (\Sigma(\tau)) & (\Sigma(\tau))_{\gamma} & & \chi & \tau & \tau
 \end{array}$$

$$\Sigma(\tau) = \bigcup_{i=0}^{\gamma-1} (\Sigma(\tau))_i.$$

[0034] In accordance with the present Invention, a near-optimal fuzzy automaton may be derived 44 for each individual separation problem using the above-described genetic algorithm. Thus, each of the fuzzy automata would learn to produce positive diagonal dominance for the signals representing its part of the problem $(\Sigma(\tau))_i$, as well as not to have diagonal dominance for the rest of the signal problem $\Sigma(\tau)$ $(\Sigma(\tau))_i$

[0035] An aggregate confusion matrix can be formed 46 from the resulting set of near-optimal fuzzy automata. The aggregate confusion matrix is used to evaluate 48 the set of fuzzy automata in view of the overall separation problem. If the set of fuzzy automata exceeds some predefined performance threshold, then the set of fuzzy automata can be used as the basis for a signal classifier. On the other hand, if the set of fuzzy automata does not exceed the performance threshold, then the separation problem is repartitioned, and the process is repeated. Likewise, the signal classifier is periodically re-evaluated over time as shown at 52 in order to ensure that its performance meets some minimum performance threshold. If the signal classifier does not exceed the performance threshold, then the above-described methodology is reapplied to the separation problem. In this way, changes in the environment are learned as the epoch is advanced.

[0036] The foregoing discussion discloses and describes merely exemplary embodiments of the present invention. One skilled in the art will readily recognize from such discussion, and from the accompanying drawings and claims, that various changes, modifications and variations can be made therein without departing from the spirit and scope of the invention as defined in the following claims.

Claims

1. A method for deriving a near-optimal fuzzy automata for a given separation problem, comprising the steps of
 - (a) forming a first generation population of fuzzy automata, where the first generation population of fuzzy automata having a plurality of fuzzy automata
 - (b) performing a mutation operation on each fuzzy automata in the first generation population of fuzzy automata
 - (c) reproducing the first generation population of fuzzy automata using a survival of the fittest operation and
 - (d) applying a cross-over operator to the reproduced first generation population of fuzzy automata, thereby yielding a next-generation population of fuzzy automata.
2. The method of Claim 1 wherein the step of forming a first generation population further comprises the step of defining each of the fuzzy automata in the first generation population as one or more matrices each having a plurality of data values, and representing in chromosome form each of the data values in at least one of the matrices in each of the fuzzy automata.
3. The method of Claim 2 wherein the step of representing in chromosome form further comprises converting each of the data values to a binary word.
4. The method of Claim 1 wherein the step of performing a mutation operation further comprises randomly flipping at least one bit in each of the fuzzy automata, where the data values for each of the fuzzy automata are represented

as a binary word.

5. The method of Claim 1 wherein the step of reproducing the first generation population further comprises the steps of

evaluating the fitness of each fuzzy automata in the first generation population of fuzzy automata
 ranking the fuzzy automata in the first generation population of fuzzy automata according to the fitness of each
 fuzzy automata and
 reproducing at least one of the fuzzy automata in accordance with a reproduction rule.

6. The method of Claim 5 wherein the step of reproducing at least one of the fuzzy automata further comprises
 defining the reproduction rule such that the two highest ranked fuzzy automata in the first generation population
 of fuzzy automata are duplicated and the lowest two ranked fuzzy automata in the first generation population of
 fuzzy automata are eliminated.

7. The method of Claim 1 wherein the step of applying a crossover operator further comprises the steps of

randomly identifying at least two of the fuzzy automata in the first generation population of fuzzy automata,
 where each of the two fuzzy automata is defined by one or more matrices each having a plurality of data values
 representing in chromosome form each of the data values in at least one of the matrices in each of the two
 fuzzy automata and
 applying a crossover operator to the at least one matrix in each of the two fuzzy automata, where the crossover
 operator determines the alleles of crossover between the two fuzzy automata, thereby yielding two next-gen-
 eration fuzzy automata.

8. The method of Claim 7 wherein the step of representing in chromosome form further comprises converting each
 of the data values to a binary word.

9. The method of Claim 7 wherein the step of applying a crossover operator further comprises a transform matrix
 having the same dimensions as the at least one matrix in each of the two fuzzy automata, where the entries in the
 transform matrix are numbers that determine the alleles of crossover in the corresponding data values of the at
 least one matrix in each of the two fuzzy automata.

10. The method according to any of the preceding claims further comprising the steps of

evaluating the performance of each fuzzy automata in the next generation of fuzzy automata in relation to the
 given separation problem and
 repeating steps (b) thru (d) until at least one fuzzy automata from the next-generation of fuzzy automata
 achieves a satisfactory performance level in relation to the given separation problem.

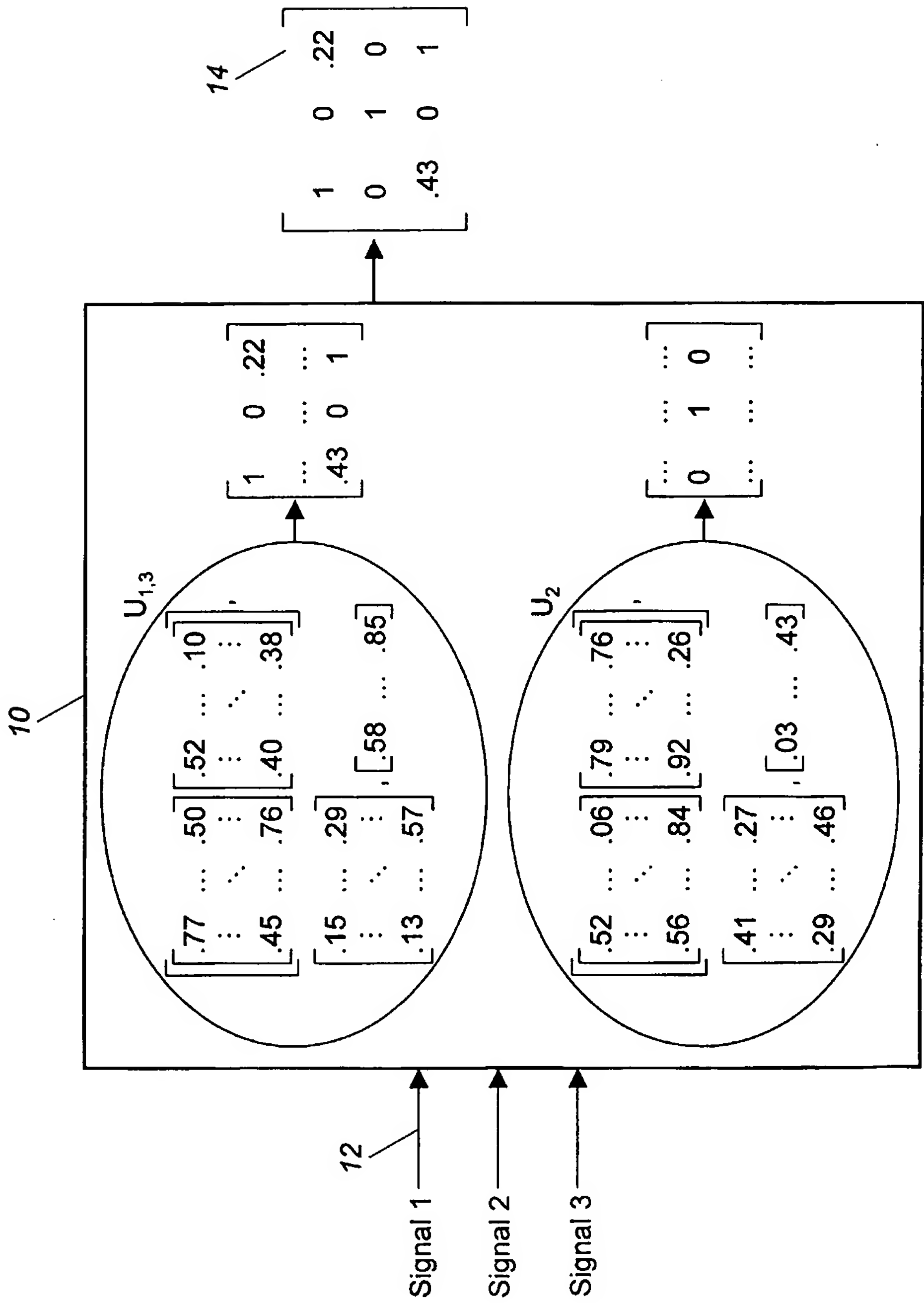


Figure 1

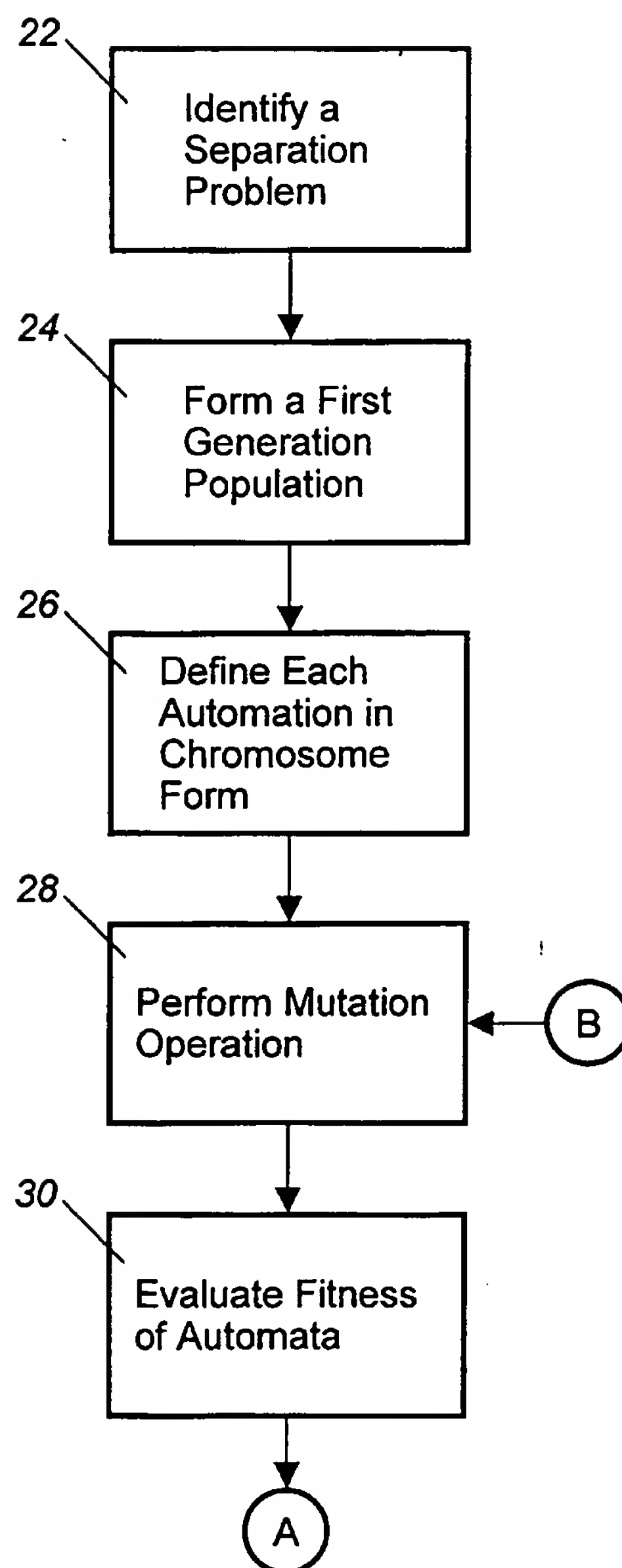


Figure 2A

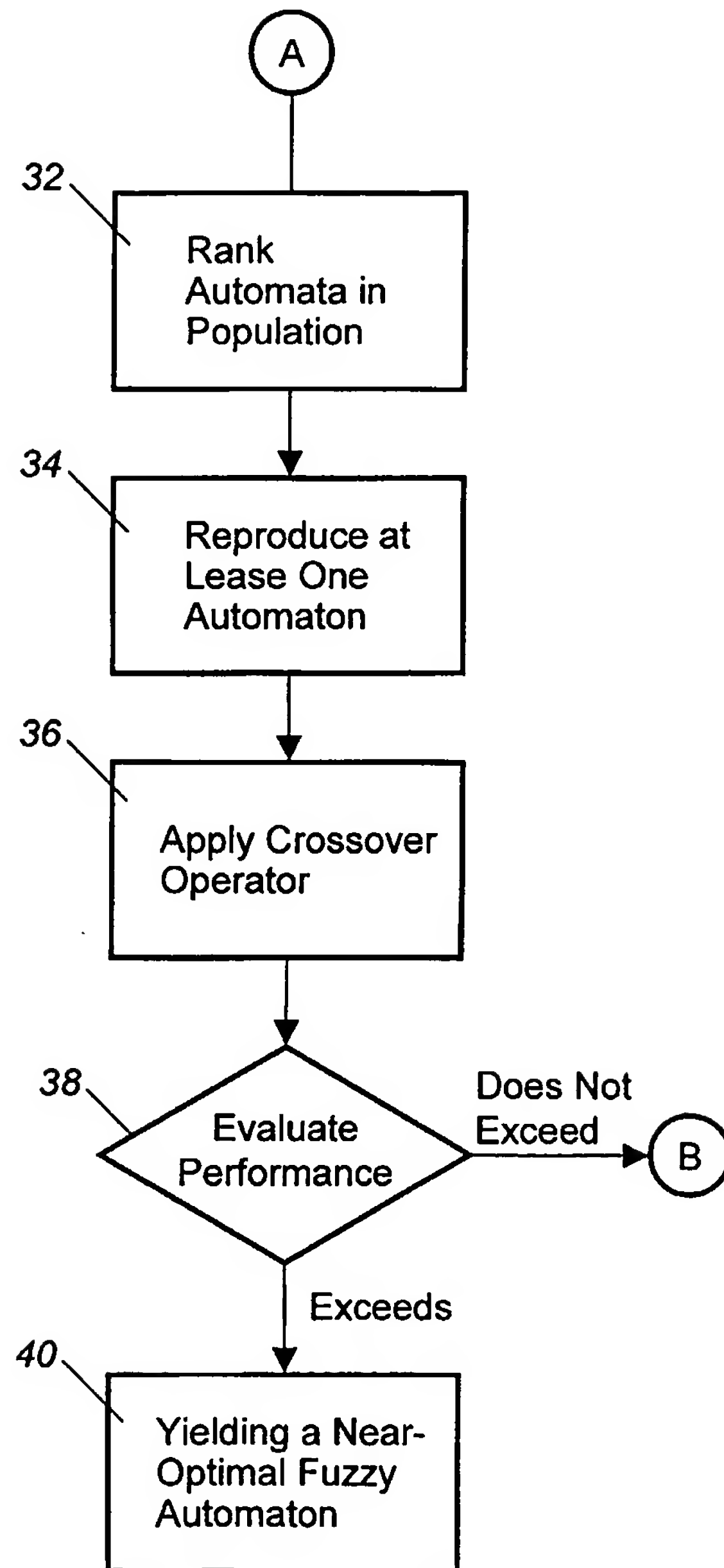


Figure 2B

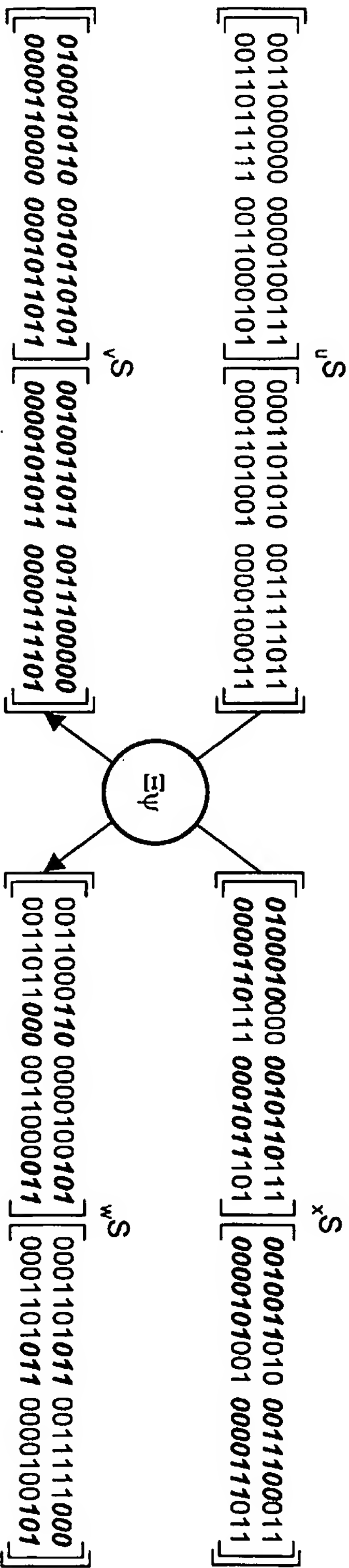


Figure 3

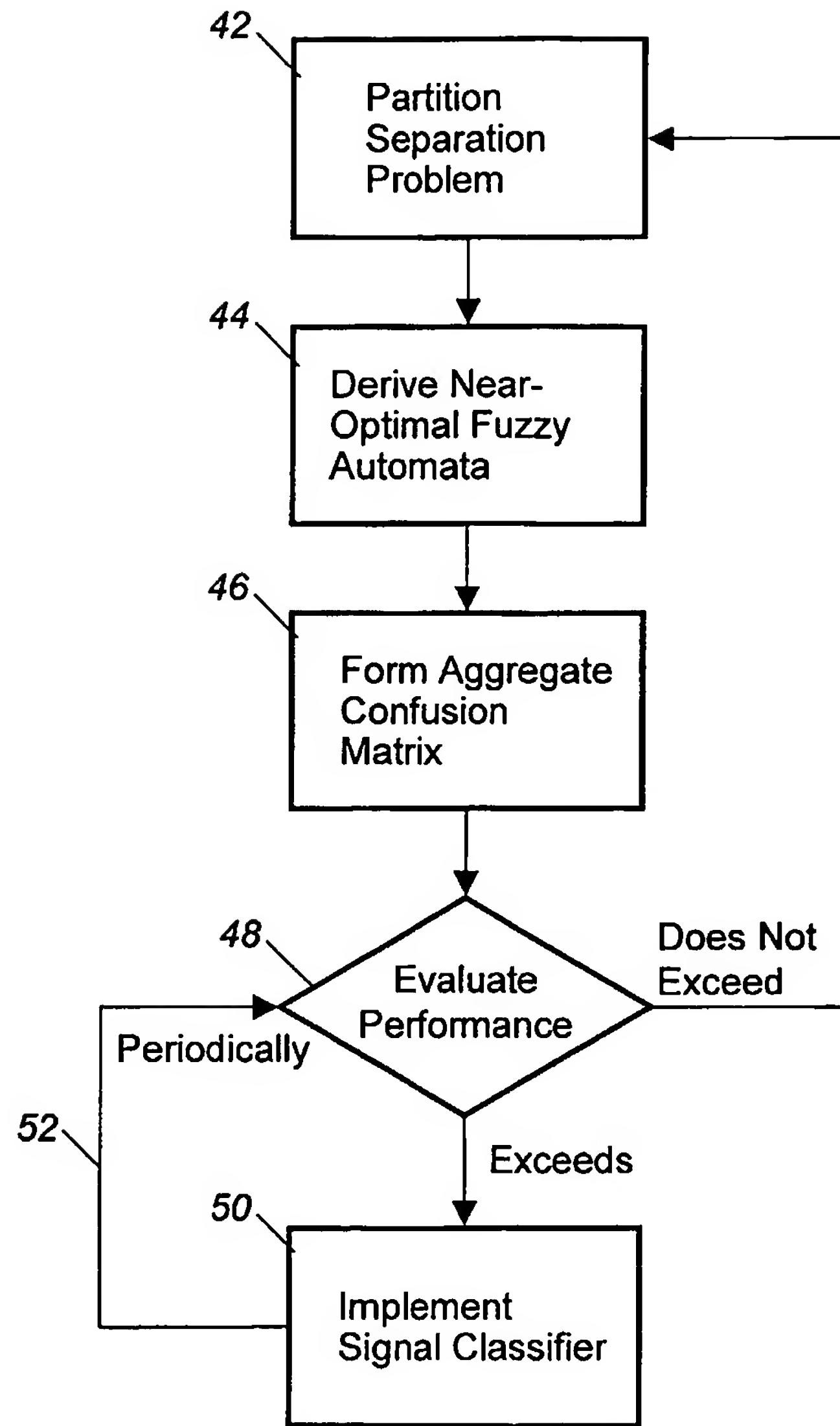


Figure 4